Dancing Distributions: Developing a Better Understanding of County-Level Crop Yield from Posterior Summaries

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Abstract
The United States Department of Agriculture's National Agricultural Statistics Service (USDA NASS) publishes annual end-of-season estimates of crop yields for a wide variety of commodity crops at the county level. These crop yields have been important determinants of payments allotted to farmers under a variety of USDA agricultural support programs. NASS is transitioning county estimates for more than a dozen commodity crops to a model-based approach. Building on Bayesian sub-area models for crop yield (Erciulescu et al., 2018) applied to Illinois corn, this poster presentation examines relevant factors of crop yield and useful posterior summaries for assessing official county-level yields from 2011-2019.

Key Words: Agricultural Statistics, Bayesian Hierarchical Models, Official Statistics, Small Area Estimation

1. Introduction

Official estimates of county-level crop yield published by USDA's National Agricultural Statistics Service (NASS) serve as important determinants and benchmarks in the administration and disbursement of agricultural support payments to qualifying farmers and ranchers in the United States. End-of-season yields are subject to several factors: technology use, the farmer's practices, and agroclimatalogical factors outside the farmer's control. The surveys supporting NASS crop county estimates are conducted post-harvest, when the events of the season will be known in finality. However, the direct estimates of yield (and acreage and total production) obtained may lack sufficient precision when respondent-provided data become sparse at the desired county-level detail.

The contribution of this work is two-fold: 1) it illustrates the utility of a Bayesian hierarchical, sub-area model for crop yield developed by Erciulescu et al. (2018) to synthesize survey and auxiliary data and quantify the uncertainty therein, and 2) it expands on the importance of accounting for agroclimatalogical variables in the production of official crop estimates. The model and available inputs are described in Section 2. The results of a model selection procedure are summarized in Section 3, and conclusions are provided in Section 4.

2. Models for County-Level Estimates of Crop Yield

County-level crop yield is one parameter of interest in the production of NASS's annual county-level crop estimates. Crop yield is a ratio of total agricultural output (production) to the total crop area successfully harvested. The necessity of this accounting identity motivated the approximate triplet benchmarking of Erciulescu et al. (2018), in which sub-area Bayesian hierarchical models for harvested area and yield were formulated. The authors

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exploited the multiplicative relationship between a model for harvested area and a model for yield, using the output to obtain Monte Carlo estimates for production. Since that publication, other Bayesian approaches that honor county-level lower bound constraints implied my administrative data on crop acreage totals have been developed to improve the accuracy of estimates of planted and harvested area (Nandram et al., 2020; Chen et al., 2020). Given a model for harvested area, the decision to model yield is part of a strategy to produce coherent estimates at all levels of aggregation, addressing one of the specific requirements of the NASS county estimates program identified in Cruze et al. (2019).

The map of the state of Illinois in Figure 1 is informative. It depicts the smallest administrative boundaries (counties) within larger contiguous boundaries known as agricultural statistics districts (ASDs). Nine specific counties are highlighted, one from within each ASD. These nine counties are emphasized in results presented in Section 3.

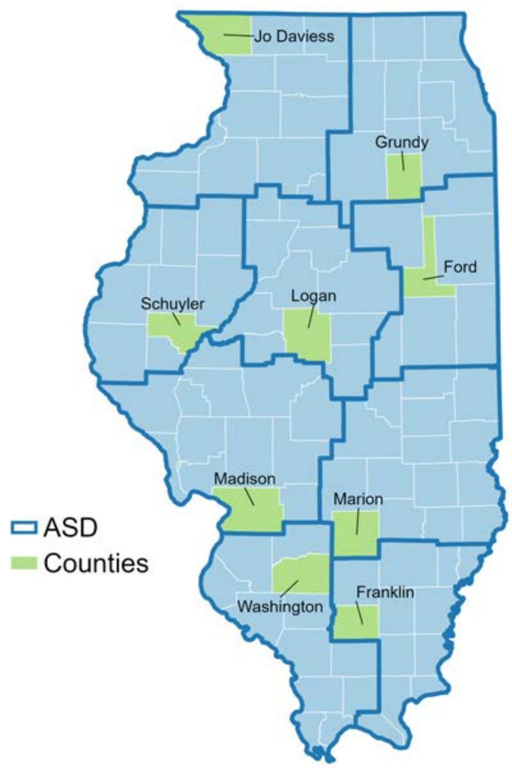

Figure 1: Map of Illinois depicting counties within agricultural statistics districts (ASD)

Letting $i \in \{1, \ldots, m\}$ and $j \in \{1, \ldots, n_i\}$ denote indices over ASDs and counties, respectively, a variation of the Erciulescu yield model is specified as follows:

$$\hat{\theta}_{ij} \overset{ind}{\sim} \text{Normal}\left(\theta_{ij}, \hat{\sigma}^2_{ij}\right), \tag{1}$$

$$\theta_{ij}|\boldsymbol{\beta}, \nu_i, \sigma^2_{\mu} \overset{ind}{\sim} \text{Normal}\left(\boldsymbol{x}'_{ij}\boldsymbol{\beta} + \nu_i, \sigma^2_{\mu}\right), \tag{2}$$

$$\nu_i \overset{ind}{\sim} \text{Normal}\left(0, \sigma^2_{\nu}\right), \tag{3}$$

where θ_{ij} denotes the quantity of interest, county-level yield in the j^{th} county within the i^{th} ASD, $\hat{\theta}_{ij}$ denotes the direct estimate of yield, and $\hat{\sigma}^2_{ij}$ denotes its corresponding estimate of the sampling variance (assumed fixed). The Bayesian model is fully specified with prior distributions for model parameters and hyperparameters where $\sigma_\mu^2 \sim \text{Uniform}\left(0, 10^8\right)$, $\sigma_\mu^2 \sim \text{Uniform}\left(0, 10^8\right)$, and $\boldsymbol{\beta} \sim \text{MVN}(\mathbf{0}, 1000 \times \hat{\boldsymbol{\Sigma}}_{\hat{\beta}})$. (The quantity $\hat{\boldsymbol{\Sigma}}_{\hat{\beta}}$ denotes the estimated covariance matrix obtained from an OLS regression of survey estimates on chosen covariates.) The sub-area model has neither explicit spatial nor temporal structure; however, the linking model in Equation 2 facilitates borrowing of information via common parameters (e.g., regression coefficients), from counties within the same ASD, and other ASDs. The random effects acknowledge that the crop yields may come from different hierarchies of populations, i.e., counties within agricultural statistics districts.

2.1 County Agricultural Production Survey Estimates

In 2011, NASS standardized its data collection in support of crops county estimates nationwide. Federally mandated crops and additional row crops and small grains crops were captured under the multivariate probability proportional to size sampling design of the County Agricultural Production Survey (CAPS). More detail about the NASS survey cycle, supported crops, and the CAPS design can be found in Cruze et al. (2019) and National Academies of Sciences, Engineering, and Medicine (2017). County-level direct estimates are available from CAPS, and their estimated sampling variances serve as plug-in estimates of sampling variance in the model above.

Examination of direct estimates of corn for the 102 counties of Illinois reveals several interesting features. Illinois is a member of the so-called 'Corn Belt', and one of the largest producers of corn in the United States. Even so, the number of reports of corn obtained varies by county, and in some cases, may be small. The number of reports received has declined over the years. This could be due in part to refining sampling protocols over the years, but like other survey organizations across the globe, NASS also faces budgetary constraints and increasing rates of nonresponse. Item nonresponse is a feature of CAPS estimates; respondents may provide information about acreage but decline to complete survey items related to yield in production. This explains the leftward shift of the boxplots for yield in Figure 2. CAPS utilizes reweighted survey estimators to account for this item nonresponse.

The lower panel in Figure 2 depicts boxplots for coefficients of variation associated with CAPS direct expansions of harvested area and with the ratio estimates of yield. The median coefficients of variation for harvested area show modest increase over time, commensurate with the reductions in reports of corn depicted in the upper panel. Coefficients of variation for yield ratios tend to be substantially smaller as the production total (numerator) is positively correlated with the harvested area (denominator) total. The boxplot for yield coefficients of variation in 2012 stands out. The 2012 crop year was characterized by a profound drought that affected much of the Corn Belt. While standard errors for county-level yields remain similar year in and year out, the magnitudes of Illinois corn yield estimates were effectively cut in half, increasing measures of relative variability in the county-yield estimates.

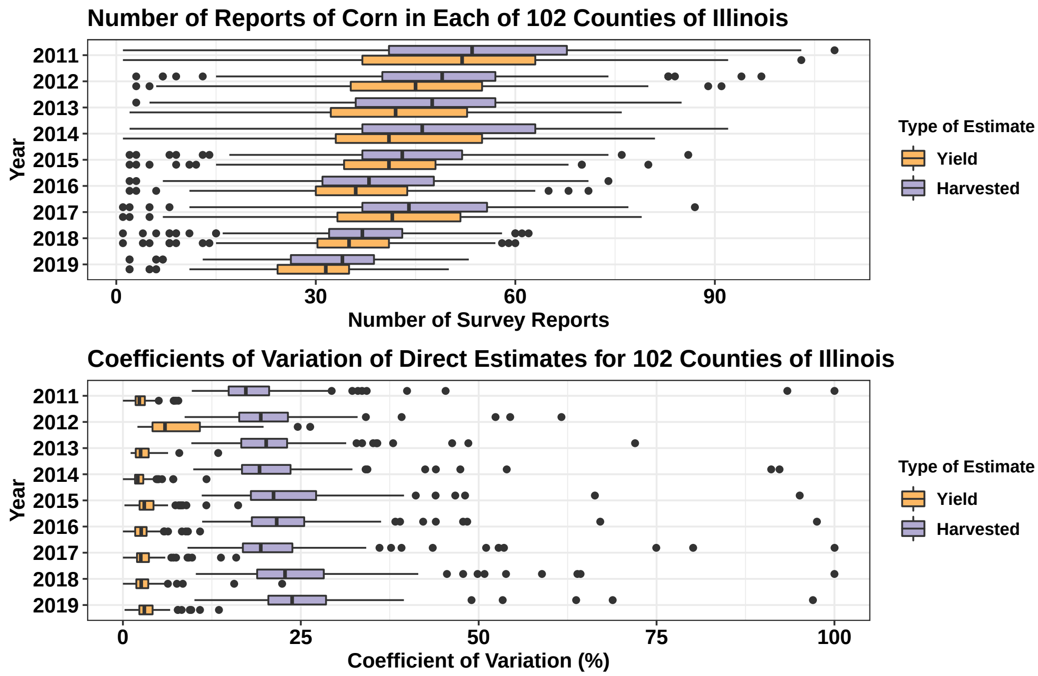

Figure 2: Number of reports of corn and coefficients of variation for CAPS corn estimates in Illinois

2.2 Potential Covariates

State-level estimates of Illinois corn yield and corn crop progress and condition are given in Table 1 for the years 2011 to 2019. A simple linear regression model of state corn yield on crop year was fit using 40 year history of official Illinois corn yields (1980 to 2019, inclusive)[1]. The trend yields reported in Table 1 are fitted values of the estimated trend equation $\widehat{\text{yield}} = 2.2\,\text{year} - 4253.8$ ($R^2 = 0.62, F_{1,38} = 63.1$); the deviations from trend (residuals) are the differences, in bushels of corn per harvested acre. Once again, 2012 stands out immediately as an anomaly. According to official progress[2] and crop condition[3] statistics, the 2012 crop year for the Illinois corn crop was characterized by conditions conducive to early planting, followed by severe drought conditions near a critical growth stage called silking (see Figure 3). This affected the quality of the crop and the total volume of corn harvested at the end of the season, resulting in diminished corn yields.

Cruze et al. (2019) discussed the importance of identifying and expanding the pool of useful covariates for yield modeling. As of this writing, NASS crop condition statistics are not available at the county level. Unlike acreage, same-year administrative data on corn yield are not available in a timely manner. While previous year estimates are available as covariates, the effects of year-over-year change on current year estimates may need to be attenuated.

Erciulescu et al. (2018) opted to use *ASD-level* precipitation totals curated by the National Oceanic and Atmospheric Administration, and the National Commodity Crop Productivity Index (NCCPI) for corn produced by USDA's Natural Resources Conservation Service, aggregated to a county-level USDA NRCS Soil Survey Staff (2019). The NCCPI is a crop-specific, soil productivity index ranging from [0,1], with values near 1 indicating

[1] Available at: https://quickstats.nass.usda.gov/results/0862C7EA-3489-3525-A588-497CD212DF38
[2] Available at: https://quickstats.nass.usda.gov/results/4751BA6B-038D-3393-87F5-B3F49EAE83FA
[3] Available at: https://quickstats.nass.usda.gov/results/1A63866D-5109-3267-90BA-45B87BDA05FD

Table 1: State-level corn yield estimates and corn crop progress for Illinois from 2011-2019. *Statistics not published during Week 40 due to lapse in federal appropriations.

Year	**Illinois State Corn Yield (bu/ac)** *NASS Official*	*Trend Yield*	*Deviation*	**Percent of Crop** *Planted Week 16*	*Silking Week 27*	*Good/Excellent Week 30*	*Mature Week 39*	*Harvested Week 40*
2011	157	171.5	-14.5	10	27	53	91	49
2012	105	173.7	-68.7	59	77	5	98	80
2013	178	175.9	2.1	1	8	64	71	*
2014	200	178.1	21.9	5	28	82	80	23
2015	175	180.3	-5.3	15	26	57	89	50
2016	197	182.5	14.5	42	53	83	97	62
2017	201	184.7	16.3	34	33	63	73	38
2018	210	186.9	23.1	4	76	80	96	63
2019	181	189.1	-8.1	1	4	44	40	13

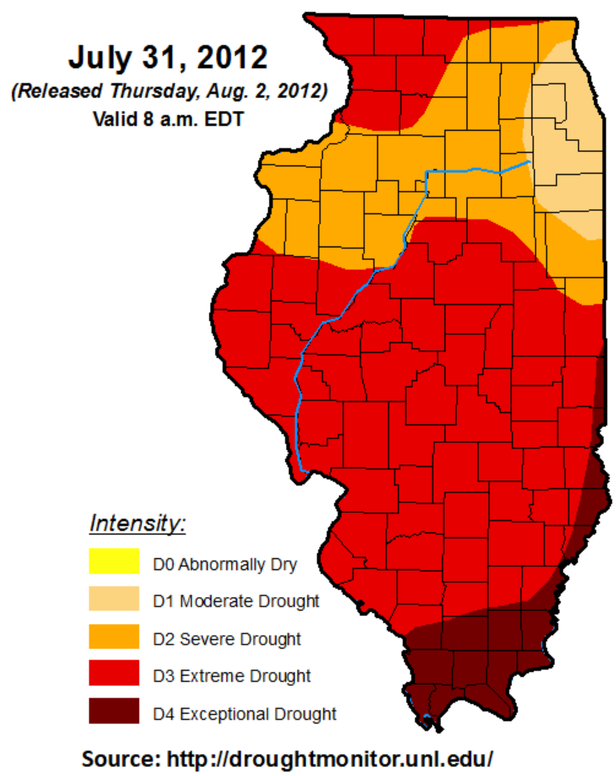

Figure 3: University of Nebraska Drought Monitor reflecting conditions at conclusion of Week 30, 2012

high levels of soil productivity for non-irrigated practices.

NCCPI is a property of soil characteristics in the county, and it is not subject to rapid fluctuation each season. In contrast, temperatures, rainfall and soil moisture profiles may differ from one growing season to the next. In addition to the NCCPI, the following *county-level* agroclimatic variables have been curated for each year and calculated by summation over the range of weeks as noted below:

- PRECIP–accumulated rainfall totals during weeks 27 to 30,
- KDD–killing degree days, a measure of heat stress accumulated above the 86F threshold during weeks 27 to 30,
- GDD–accumulated growing degree days over the 50F degree threshold accumulated from weeks 16 to 40,
- ARID–the agricultural reference index for drought described by Woli et al. (2012) accumulated over weeks 16 to 40.

The ranges of weeks chosen reflect agronomic understanding about several factors that contribute along the life cycle of the Illinois corn crop. (See, e.g., (Nafziger, 2009, Ch.2) for more agronomic background on Illinois corn crop.) Weeks 16 to 40 encompass 'typical' activities from planting to the onset of maturity. Weeks 27 to 30 approximate the window around the reproductive silking stage, when the corn crop is particularly susceptible to combinations of heat stress and lack of soil moisture.

3. Results

3.1 Covariates Selection

The pool of covariates identified above is not exhaustive. A number of additional (and likely positively correlated) covariates may also be available. In addition to main effects, interaction terms may be of interest. The idea of sparsity, that only a few of many potential explanatory variables exert the most impact on the model, is worthy of exploration.

Accordingly, the ordinary least squares regression model below guides the search for sets of covariates to be permitted into the Bayesian sub-area model for yield:

$$\begin{aligned} \text{yield} = \beta_0 + \beta_1\text{NCCPI} + \beta_2\text{GDD} + \beta_3\text{PRECIP} + \beta_4\text{KDD} + \beta_5\text{ARID} \\ + \beta_6\frac{\text{KDD}}{\text{PRECIP}} + \beta_7(\text{KDD} \times \text{ARID}) + \varepsilon. \end{aligned} \tag{4}$$

As separate models are to be fit for each year, all possible submodels of Equation 4 constitute $2^6 = 64$ possible models per year (excluding an intercept only model, and allowing for the possibility of interaction terms without main effects). Rather than fitting 64 Bayesian models per year, exploration of all combinations of covariates was facilitated by regression using the `dredge` function from the R software's `MuMIn` package (Bartón, 2020). (Recall that whatever the choice of covariates, the estimated covariance matrix $\widehat{\boldsymbol{\Sigma}}_{\hat{\boldsymbol{\beta}}}$ is part of the prior specification in the Bayesian model as well.) All possible sub-models of Equation 4 were fit to survey yield estimates and covariates data, separately for each year. The models were ranked in terms of Bayesian Information Criterion (BIC), and the explanatory variables identified by the best performing model in terms of BIC were selected as candidates as input into the Bayesian models for yield. For all years, a more parsimonious model consisting only of intercept and NCCPI is also reported, as this variable is selected in all of the top performing models and it explains appreciable amounts of the variation in the yield survey data each year. The list of variables, R^2 and BIC are shown in Table 2.

Table 2: Summaries of linear regressions used to identify covariates of interest

Year	Intercept+NCCPI		BIC Chosen Model		
	R^2	*BIC*	R^2	*BIC*	*Variables Admitted*
2011	0.35	876.0	0.70	800.7	Intercept, NCCPI, KDD
2012	0.41	1,009.8	0.83	894.2	Intercept, NCCPI, GDD, KDD
2013	0.34	820.9	0.48	806.1	Intercept, NCCPI, PRECIP, KDD
2014	0.49	835.0	0.60	818.3	Intercept, NCCPI, GDD, KDD
2015	0.28	914.8	0.43	905.9	Intercept, NCCPI, PRECIP, KDD
2016	0.51	954.9	0.77	883.6	Intercept, NCCPI, KDD
2017	0.40	936.5	0.61	905.5	Intercept, NCCPI, KDD, ARID, KDD×ARID
2018	0.42	927.0	0.72	869.1	Intercept, NCCPI, GDD, PRECIP, KDD, (KDD÷PRECIP)
2019	0.35	874.0	0.52	860.2	Intercept, NCCPI, PRECIP, KDD, ARID, (KDD÷PRECIP)

3.2 Model Selection

The procedures above for identifying covariates lead to two presumptive Bayesian models of yield per year, one incorporating only intercept and NCCPI, and the other representing an expanded set of covariates as noted in last column of Table 2. For brevity, the latter is referred to as the 'alternative' model.

The Bayesian hierarchical models were fit by Markov chain Monte Carlo simulation using R and JAGS software. For each combination of year and choice of covariates, simulations consisting of three chains, each with 30,000 Monte Carlo iterates were constructed. The first 5,000 iterates of each chain were discarded as burn-in, and the remaining iterates from each chain were subject to a systematic thinning, retaining every 25th sample. A total of 3,000 iterates were used to construct posterior summaries.

The deviance information criterion (DIC) and convergence diagnostics for all model parameters (all 102 county-level yields, θ_{ij}, regression coefficients, $\boldsymbol{\beta}$, and variance components, σ^2_ν and σ^2_μ) were assessed. In all cases, potential scale reduction factors were near unity. Effective sample sizes are acceptably close to 3,000, indicating appropriate mixing of chains. In Table 3, the smaller values of DIC, emphasized in bold, indicate the preferred model based on goodness of fit. The posterior summaries reported for each year in Section 3.3 are with respect to the models indicated in bold: expanded models in 2012, 2017, and 2018, and models with NCCPI as sole covariate in all other years. For brevity, posterior means and standard deviations, percentiles of the posterior distributions, and the potential scale reduction factors ($\hat{R}$) and effective sample sizes (ESS) for the nuisance parameters of each model are reported in Appendix A.

Table 3: Deviance information criterion (DIC) for candidate models

Year	NCCPI	Alternative
2011	**645.1**	650.4
2012	713.1	**711.9**
2013	**696.7**	697.0
2014	**683.5**	689.9
2015	**728.4**	735.9
2016	**704.8**	704.9
2017	736.6	**731.7**
2018	731.1	**729.8**
2019	**740.3**	746.5

3.3 Expressing the Uncertainty of Modeled Estimates of Yield

Historically, NASS county estimates have been published without accompanying measures of uncertainty[4]. The Bayesian models offer a means of synthesizing NASS CAPS survey estimates with other relevant data in a repeatable manner that also gives rise to descriptions of uncertainty.

For clarity in plotting, posterior distributions of county corn yields for nine counties (one from each ASD in Illinois) are plotted across years 2011 to 2019 in Figure 4. The counties are sorted approximately from North (Jo Daviess County) to South (Franklin County). While the covariates included in each year's selected model may differ, tracing the distributions through time shows the change in yield each season, particularly the sharp reduction in yields in the 2012 drought year. The spread of posterior distributions changes each year due to sampling variance (different units may be selected) and differences in growing conditions. Although the models have no explicit spatial dependence structure, some spatial trend, the tendency of southern counties to have lower yield relative to northern counties and to the state yield, is still apparent.

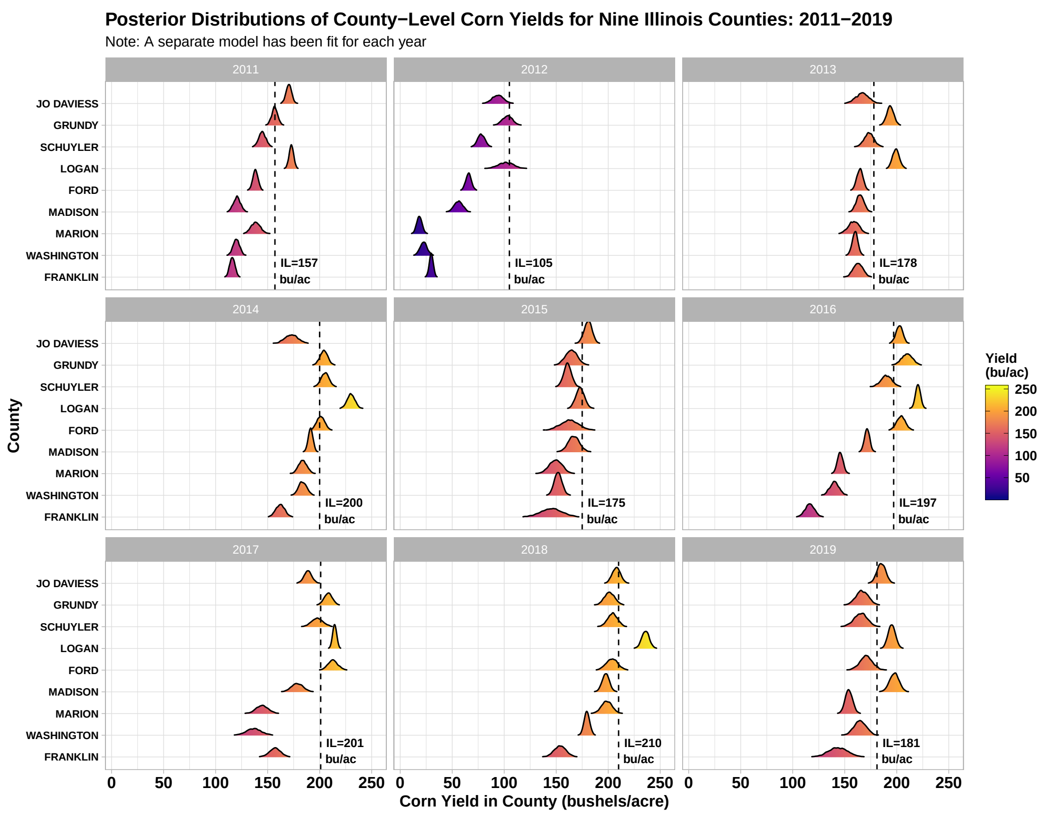

Figure 4: Posterior distributions of county-level corn yield. The vertical dashed line denotes the official Illinois *state-level* corn yield estimate.

In addition to the modeled point estimate of county-level corn yield (posterior mean), the posterior distribution for 2012 corn yield in Jo Daviess shown in Figure 4 can be used to construct meaningful interval estimates. Also plotted, the published 2012 annual county estimate, and a point estimate derived from NASS's gold standard data collection, the Census of Agriculture, both fall within a stringent 50% highest density interval; for this county, the

[4]IL county corn yields, 2011-2019: https://quickstats.nass.usda.gov/results/5A6E214E-6C0E-3C43-9028-7A7F4F42F6B6

model estimate is slightly closer to the Census yield than the official NASS annual estimate is.[5]

NASS has traditionally produced tabular data consisting only of official point estimates. While dissemination of entire distributions poses some interesting challenges for the breadth of estimates NASS must publish, functions of standard error (model posterior standard deviation) can be readily calculated and disseminated along with the point estimates. As NASS transitions to a system of model-based county estimates, the focus has been on providing coefficients of variation along with the point estimates. Figure 6 summarizes the improvement in relative variability achieved based on modeling; note in particular the reductions in coefficients of variation for the upper quartile and some of the outliers.

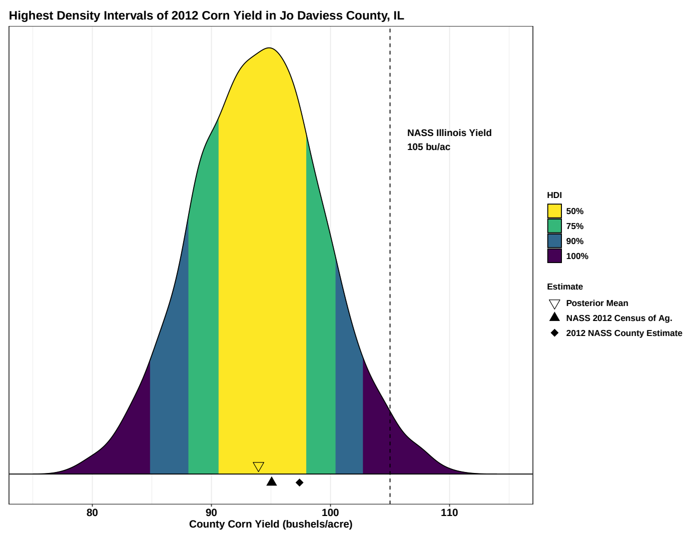

Figure 5: Posterior distribution and regions of highest posterior density for corn yield in Jo Daviess, IL, 2012

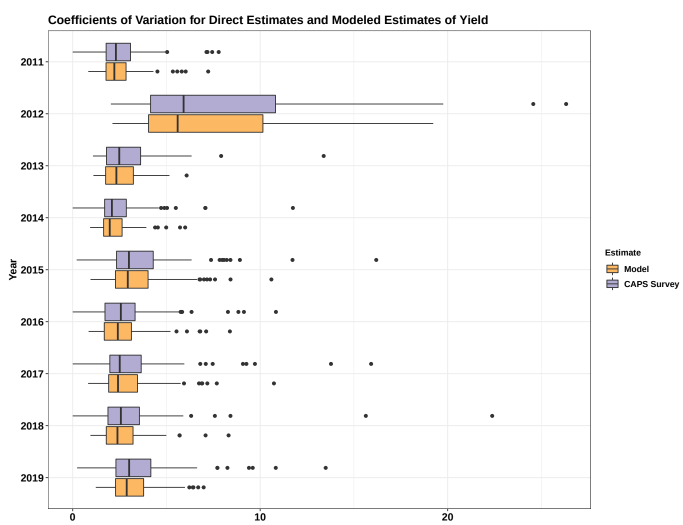

Figure 6: Comparison of coefficients of variation for direct estimates and model-based estimates of county-level corn yield

[5] Census of Agriculture yield point estimates reported are the ratio of the production to harvested area totals: https://quickstats.nass.usda.gov/results/E568388B-1F2C-38F2-B27A-1A406C12FBAB

4. Discussion and Future Work

The presented sub-area Bayesian hiearchical model for county-level corn yields has the potential to synthesize NASS survey estimates with other types of data in a repeatable manner while quantifying the uncertainty associated with the estimates. A model incorporating a soil productivity index showed reasonable peformance over a range of years. In years 2012, 2017, and 2018, the selected models incorporated additional agroclimatic covariates to improve the accuracy and precision of the resulting yield estimates.

The Illinois corn crop represents just one commodity of interest in one state, whereas support for NASS's entire county estimates program entails producing estimates for more than a dozen distinct types of crops each year. As of this writing, county estimates for major row crops are to be produced in 41 states and for small grains commodities in 32 states. From the practical point of view, options that can 'automate' covariates selection for yield models each year or help identify models that perform well over the widest range of conditions are beneficial for producing the volume of official statistics that NASS must deliver annually. Crop simulation models designed to understand causes of rapid vegetative development or sharp decreases in yield potential could help identify anomalous events, especially where yield models may need tuning. Future work may also include investigation of the use of principal components analysis or independent components analysis for retaining as much relevant agroclimatic information as possible in a smaller number of covariates.

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References

Bartón, K. (2020). MuMIn: Multi-Model Inference, V 1.43.17. URL: https://CRAN.R-project.org/package=MuMIn.

Chen, L., Nandram, B., and Cruze, N. (2020). Hierarchical Bayesian Model with Inequality Constraints for County Estimates. In *Proceedings of the Joint Statistical Meetings, Government Statistics Section*. American Statistical Association, Alexandria, VA. Appearing in this proceedings.

Cruze, N. B., Erciulescu, A. L., Nandram, B., Barboza, W. J., and Young, L. J. (2019). Producing Official County-Level Agricultural Estimates in the United States: Needs and Challenges. *Statistical Science*, 34:301–316.

Erciulescu, A. L., Cruze, N. B., and Nandram, B. (2018). Benchmarking a triplet of official estimates. *Environmental and Ecological Statistics*, 25(4):523–547.

Nafziger, E. (2009). Corn. In *Illinois Agronomy Handbook*, chapter 2. University of Illinois at Urbana-Champaign, College of Agriculture, Cooperative Extension Service, Urbana, IL, 24 edition.

Nandram, B., Cruze, N., and Erciulescu, A. (2020). Bayesian Benchmarking under Inequality Constraints and Double Shrinkage. USDA NASS Working Paper.

National Academies of Sciences, Engineering, and Medicine (2017). *Improving Crop Estimates by Integrating Multiple Data Sources*. The National Academies Press, Washington, DC.

USDA NRCS Soil Survey Staff (2019). United States Department of Agriculture Natural Resources Conservation Service Soil Survey Geographic (SSURGO) Database, FY2019 release. URL: https://sdmdataaccess.sc.egov.usda.gov.

Woli, P., Jones, J., Ingram, K., and Fraisse, C. (2012). Agricultural Reference Index for Drought (ARID). *Agronomy Journal*, 104:287–300.

A. Appendix

Table 4: Posterior summaries and convergence diagnostics for nuisance parameters of selected models for corn yield

Year	Parameter	Posterior Mean	Posterior Std. Dev.	Percentile of Posterior Distribution 2.50%	25%	50%	75%	97.50%	$\hat{R}$	ESS
2011	$\beta_{\text{INTERCEPT}}$	97.029	13.321	70.604	88.336	96.982	105.553	123.802	1.001	3000
	β_{NCCPI}	73.855	16.598	40.764	62.851	73.814	84.691	106.282	1.001	3000
	σ^2_μ	123.024	20.965	88.711	107.955	120.713	135.554	170.251	1.001	3000
	σ^2_ν	406.277	488.586	101.74	192.266	296.113	467.47	1337.921	1.001	2500
2012	$\beta_{\text{INTERCEPT}}$	31.767	52.87	-67.805	-4.239	30.329	66.486	134.053	1.001	3000
	β_{NCCPI}	155.885	23.304	111.462	140.057	155.578	171.043	202.339	1.004	1800
	β_{GDD}	0.033	0.018	-0.002	0.021	0.034	0.046	0.068	1.001	3000
	β_{KDD}	-0.668	0.082	-0.832	-0.722	-0.668	-0.611	-0.508	1.001	3000
	σ^2_μ	227.773	39.526	161.401	200.177	223.29	251.919	317.345	1.001	3000
	σ^2_ν	262.297	340.808	41.976	109.838	178.23	298.149	998.73	1.001	3000
2013	$\beta_{\text{INTERCEPT}}$	108.171	11.751	85.063	100.4	108.013	116.317	131.278	1.001	2700
	β_{NCCPI}	91.052	16.446	59.161	79.737	90.959	102.033	124.288	1.001	2800
	σ^2_μ	130.991	23.614	91.124	114.92	128.481	145.241	182.702	1.001	3000
	σ^2_ν	37.314	43.096	1.999	12.301	24.718	46.086	150.14	1.001	3000
2014	$\beta_{\text{INTERCEPT}}$	116.125	12.85	90.971	107.271	115.987	124.807	141.359	1.002	1600
	β_{NCCPI}	110.197	17.394	75.686	98.209	110.26	122.026	144.204	1.001	2400
	σ^2_μ	123.539	21.814	87.665	108.602	121.547	136.068	171.775	1.001	3000
	σ^2_ν	138.83	153.93	24.232	61.492	99.627	161.144	490.447	1.001	3000
2015	$\beta_{\text{INTERCEPT}}$	87.83	18.368	53.082	75.737	87.328	99.299	124.557	1.001	3000
	β_{NCCPI}	114.317	25.47	63.825	97.894	115.011	131.029	163.387	1.001	3000
	σ^2_μ	330.736	54.792	241.152	292.386	325.252	362.688	453.162	1.001	3000
	σ^2_ν	169.297	173.011	24.034	73.033	121.744	203.295	601.893	1.001	3000
2016	$\beta_{\text{INTERCEPT}}$	96.042	18.048	60.691	84.169	95.421	107.833	132.938	1.001	3000
	β_{NCCPI}	126.968	20.28	87.542	113.098	127.215	140.534	167.125	1.001	3000
	σ^2_μ	188.228	32.312	134.623	165.238	185.383	207.327	258.691	1.002	1500
	σ^2_ν	1198.779	950.91	332.44	621.847	920.979	1436.585	3780.343	1.001	3000
2017	$\beta_{\text{INTERCEPT}}$	75.6	29.929	17.992	55.931	75.246	95.328	134.914	1.001	2200
	β_{NCCPI}	117.9	23.734	72.129	101.906	117.319	134.3	164.024	1.001	3000
	β_{ARID}	0.73	0.42	-0.071	0.449	0.727	1.011	1.563	1.001	3000
	β_{KDD}	0.908	0.351	0.236	0.672	0.904	1.15	1.594	1.002	1400
	$\beta_{\text{ARID*KDD}}$	-0.016	0.005	-0.026	-0.02	-0.016	-0.013	-0.007	1.002	1600
	σ^2_μ	225.113	40.744	156.392	196.237	220.708	251.03	315.21	1.001	3000
	σ^2_ν	195.139	188.796	27.053	82.733	140.531	242.23	707.371	1.002	1500
2018	$\beta_{\text{INTERCEPT}}$	-61.385	42.056	-143.89	-89.6	-60.845	-33.441	20.419	1.001	3000
	β_{NCCPI}	45.911	20.194	7.655	32.611	45.393	59.284	85.468	1.001	3000
	β_{GDD}	0.073	0.014	0.047	0.064	0.073	0.082	0.099	1.001	3000
	β_{KDD}	-1.36	0.186	-1.73	-1.481	-1.357	-1.236	-0.99	1.001	3000
	β_{PRECIP}	9.93	2.92	4.124	7.934	9.975	11.928	15.764	1.001	3000
	$\beta_{\text{KDD/PRECIP}}$	0.301	0.094	0.12	0.236	0.301	0.366	0.484	1.001	3000
	σ^2_μ	127.101	25.759	84.84	108.977	124.534	142.779	185.37	1.001	3000
	σ^2_ν	200.74	202.277	34.159	86.465	143.849	237.29	740.061	1.002	1800
2019	$\beta_{\text{INTERCEPT}}$	123.672	14.99	94.347	113.588	123.897	133.832	152.708	1.001	3000
	β_{NCCPI}	72.006	20.378	33.381	57.95	71.69	85.799	111.687	1.002	2100
	σ^2_μ	168.305	31.411	115.978	145.808	164.714	188.13	238.384	1.001	3000
	σ^2_ν	223.084	212.891	46.739	102.708	165.279	264.191	775.993	1.001	2400